PREDICTING HOUSE PRICE USING MACHINE LEARNING

Phase-4 submission document

Project Title: House Price Predictor

Phase 4: *Development Part 2*

Topic: *Continue building the house price prediction model by feature engineering, model training, and evaluation.*

Introduction:

Predicting the price of a house may seem like a complex task, but with the right guidance, it can become more accessible. This beginner's guide is designed to help you understand the process of house price prediction. We'll break it down into the following key components:

Choosing the Right Features

Introduction to Feature Selection

The first step in predicting house prices is selecting the right aspects or "features" of a house that influence its value. In this section, we'll explain how to identify and choose the most important features that matter, such as the number of bedrooms, the neighborhood, and more.

Training Your Model

Understanding Model Training

Once you've selected your features, it's time to teach a computer how to use this information to make predictions. In this part, we'll demystify the process of training a machine learning model to estimate house prices accurately.

Evaluating Model Performance

Assessing Your Model

After the model has been trained, it's crucial to assess its performance to ensure it makes accurate predictions for new houses. This section will guide you through the evaluation process, highlighting the significance of testing your model on unseen data.

In the forthcoming sections, we will delve deeper into each of these components, offering clear and straightforward explanations to help you get started with house price prediction, even if you're new to the field.

Given data set:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386
...	...	...	...	...	...	...	...
4995	60567.944140	7.830362	6.137356	3.46	22837.361035	1.060194e+06	USNS Williams\nFPO AP 30153-7653
4996	78491.275435	6.999135	6.576763	4.02	25616.115489	1.482618e+06	PSC 9258, Box 8489\nAPO AA 42991-3352
4997	63390.686886	7.250591	4.805081	2.13	33266.145490	1.030730e+06	4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4998	68001.331235	5.534388	7.130144	5.44	42625.620156	1.198657e+06	USS Wallace\nFPO AE 73316
4999	65510.581804	5.992305	6.792336	4.07	46501.283803	1.298950e+06	37778 George Ridges Apt. 509\nEast Holly, NV 2...

5000 Rows x 7 Columns

How to Predict House Prices: A Simple Overview

1. **Get the Data Ready:**
   - First, clean up the data by fixing any messy or incorrect information.
   - Remove any extreme values (outliers) that could skew your predictions.
   - Fill in any missing data where details are incomplete.
2. **Choose the Important Details:**
   - Select the specific house details that matter the most for predicting its price.
   - Use methods like checking which details are related to each other or removing less useful ones.
3. **Teach a Computer:**
   - Now, it's time to teach a computer to guess house prices.
   - Think of it like explaining to the computer how to use the important details you've picked to make predictions.

4. **See If It's Good at Guessing:**
    - Test your computer's predictions by checking how close they are to the actual prices.
    - You can measure this with something called "mean squared error" or "root mean squared error."
5. **Put It to Work:**
    - If your computer is making good predictions, you can use it to tell you how much a new house is worth.

How to Choose the Right House Details for Price Prediction:

1. **Pick the Thing You Want to Guess:**

First, decide what you want to predict; in our case, it's the house price.

2. **Explore the Details:**

Look at all the information you have about houses.
Use things like pictures, charts, and comparisons to understand which house details might help you predict the price.

3. **Find Duplicate Information:**

If you see two details that seem to say the same thing, you can get rid of one. They probably tell you the same stuff.

4. **Skip What Doesn't Help:**

If some details don't seem to matter when figuring out the price, you can just ignore them. They're not going to be useful.

Feature Selection:

We are selecting numerical features which have more than 0.50 or less than -0.50 correlation rate based on Pearson Correlation Method—which is the default value of parameter "method" in corr() function. As for selecting categorical features, I selected the categorical values which I believe have significant effect on the target variable such as Heating and MSZoning.

In [1]:

```
important_num_cols = list(df.corr()["SalePrice"][(df.corr()["SalePrice"]>0.50) | (df.corr()["SalePrice"]<-0.50)].index)

cat_cols = ["MSZoning", "Utilities","BldgType","Heating","KitchenQual","SaleCondition","LandSlope"]

important_cols = important_num_cols + cat_cols

df = df[important_cols]
```

Checking for the missing values

In [2]:

```
print("Missing Values by Column")

print("-"*30)

print(df.isna().sum())

print("-"*30)

print("TOTAL MISSING VALUES:",df.isna().sum().sum())
```

Missing Values by Column

OverallQual 0
YearBuilt 0
YearRemodAdd 0
TotalBsmtSF 0
1stFlrSF 0
GrLivArea 0
FullBath 0
TotRmsAbvGrd 0
GarageCars 0
GarageArea 0
SalePrice 0
MSZoning 0
Utilities 0
BldgType 0
Heating 0
KitchenQual 0
SaleCondition 0
LandSlope 0

dtype: int64

TOTAL MISSING VALUES: 0

Model training:

1. **Choose a machine learning algorithm.** There are a number of different machine learning algorithms that can be used for house price prediction, such as linear regression, ridge regression, lasso regression, decision trees, and random forests are Covered above.

Machine Learning Models:

In [3]:

```
models = pd.DataFrame(columns=["Model","MAE","MSE","RMSE","R2 Score","RMSE (Cross-Validation)"])
```

Linear Regression:

In [4]:

```
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
predictions = lin_reg.predict(X_test)
mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(lin_reg)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "LinearRegression","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_crossval}models = models.append(new_row, ignore_index=True)
```

Out[4]:

MAE: 23567.890565943395
MSE: 1414931404.6297863
RMSE: 37615.57396384889
R2 Score: 0.8155317822983865

RMSE Cross-Validation: 36326.451444669496

Ridge Regression:

In [5]:

```
ridge = Ridge()ridge.fit(X_train, y_train)predictions = ridge.predict(X_test)
mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(ridge)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "Ridge","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}models = models.append(new_row, ignore_index=True)
```

Out[5]:

MAE: 23435.50371200822
MSE: 1404264216.8595588
RMSE: 37473.513537691644
R2 Score: 0.8169224907874508

RMSE Cross-Validation: 35887.852791598336

Lasso Regression:

In [6]:

```
lasso = Lasso()lasso.fit(X_train, y_train)predictions = lasso.predict(X_test)
mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(lasso)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "Lasso","MAE": mae, "MSE": mse, "RMSE": rmse,
"R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}model
s = models.append(new_row, ignore_index=True)
```

Out[6]:

MAE: 23560.45808027236
MSE: 1414337628.502095
RMSE: 37607.680445649596
R2 Score: 0.815609194407292

RMSE Cross-Validation: 35922.76936876075

Elastic_Net:

In [7]:

```
elastic_net = ElasticNet()elastic_net.fit(X_train, y_train)predictions =
elastic_net.predict(X_test)
mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(elastic_net)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "ElasticNet","MAE": mae, "MSE": mse, "RMSE": r
mse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}
models = models.append(new_row, ignore_index=True)
```

Out[7]:

MAE: 23792.743784996732
MSE: 1718445790.1371393
RMSE: 41454.14080809225
R2 Score: 0.775961837382229

RMSE Cross-Validation: 38449.00864609558

Support Vector Machines:

In [8]:

```
svr = SVR(C=100000)svr.fit(X_train, y_train)predictions =
svr.predict(X_test) mae, mse, rmse, r_squared = evaluation(y_test,
predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(svr)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "SVR","MAE": mae, "MSE": mse, "RMSE": rmse, "
R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}models
 = models.append(new_row, ignore_index=True)
```

Out[9]:

MAE: 17843.16228084976
MSE: 1132136370.3413317
RMSE: 33647.234215330864
R2 Score: 0.852400492526574

RMSE Cross-Validation: 30745.475239075837

Random_Forest_Regressor:

In [9]:

```
random_forest = RandomForestRegressor(n_estimators=100)random_forest.
fit(X_train, y_train)predictions = random_forest.predict(X_test)mae, mse,
rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(random_forest)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "RandomForestRegressor","MAE": mae, "MSE":
mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)":
rmse_cross_val}models = models.append(new_row, ignore_index=True)
```

Out[9]:

```
MAE: 18115.11067351598
MSE: 1004422414.0219476
RMSE: 31692.623968708358
R2 Score: 0.869050886899595
```

RMSE Cross-Validation: 31138.863315259332

XGBoost Regressor:

In [10]:

```
xgb = XGBRegressor(n_estimators=1000, learning_rate=0.01)xgb.fit(X_train, y_train)predictions = xgb.predict(X_test) mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(xgb)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "XGBRegressor","MAE": mae, "MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validation)": rmse_cross_val}models = models.append(new_row, ignore_index=True)
```

Out[10]:

```
MAE: 17439.918396832192
MSE: 716579004.5214689
RMSE: 26768.993341578403
R2 Score: 0.9065777666861116
```

```
RMSE Cross-Validation: 29698.84961808251
```

Polynomial Regression (Degree=2)

In [11]:

```
poly_reg = PolynomialFeatures(degree=2)X_train_2d = poly_reg.fit_transfo
rm(X_train)X_test_2d = poly_reg.transform(X_test) lin_reg =
LinearRegression()lin_reg.fit(X_train_2d, y_train)predictions =
lin_reg.predict(X_test_2d)
mae, mse, rmse, r_squared = evaluation(y_test, predictions)
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r_squared)
print("-"*30)rmse_cross_val = rmse_cv(lin_reg)
print("RMSE Cross-Validation:", rmse_cross_val)
new_row = {"Model": "Polynomial Regression (degree=2)","MAE": mae, "
MSE": mse, "RMSE": rmse, "R2 Score": r_squared, "RMSE (Cross-Validat
ion)":
rmse_cross_val}models = models.append(new_row, ignore_index=True)
```

Out[11]:

```
MAE: 2382228327828308.5
MSE: 1.5139911544182342e+32
RMSE: 1.230443478758059e+16

R2 Score: -1.9738289005226644e+22

--------------------------------------------------

RMSE Cross-Validation: 36326.451444669496
```

Model training:

- Model training is the process of teaching a machine learning model to predict house prices. It involves feeding the model historical data on house prices and features, such as square footage, number of bedrooms, and location. The model then learns the relationships between these features and house prices.
- Once the model is trained, it can be used to predict house prices for new data. For example, you could use the model to predict the price of a house that you are interested in buying.

1. **Prepare the data.** This involves cleaning the data, removing any errors or inconsistencies, and transforming the data into a format that is compatible with the machine learning algorithm that you will be using.
2. **Split the data into training and test sets.** The training set will be used to train the model, and the test set will be used to evaluate the performance of the model on unseen data.
3. **Choose a machine learning algorithm.** There are a number of different machine learning algorithms that can be used for house price prediction, such as linear regression, ridge regression, lasso regression, decision trees, and random forests.
4. **Tune the hyperparameters of the algorithm.** The hyperparameters of a machine learning algorithm are parameters that control the learning process. It is important to tune the hyperparameters of the algorithm to optimize its performance.

5. **Train the model on the training set.** This involves feeding the training data to the model and allowing it to learn the relationships between the features and house prices.
6. **Evaluate the model on the test set.** This involves feeding the test data to the model and measuring how well it predicts the house prices.

If the model performs well on the test set, then you can be confident that it will generalize well to new data.

Dividing Dataset in to features and target variable:

In [12]:

```
X = dataset[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms', 'Avg. Area Number of Bedrooms', 'Area Population']]
Y = dataset['Price']
```

2. **Split the data into training and test sets.** The training set will beused to train the model, and the test set will be used to evaluate the performance of the model.

In [13]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=101)
```

In [14]:

```
Y_train.head()
```

Out[14]:

3413 1.305210e+06

1610 1.400961e+06

3459 1.048640e+06

4293 1.231157e+06

1039 1.391233e+06

Name: Price, dtype: float64

In [15]:

```
Y_train.shape
```

Out[15]:

(4000,)

In [16]:

```
Y_test.head()
```

Out[16]:

1718 1.251689e+06

2511 8.730483e+05

345 1.696978e+06

2521 1.063964e+06

54 9.487883e+05

Name: Price, dtype: float64

In [17]:

```
Y_test.shape
```

Out[17]: (1000)

3. **Train the model on the training set.** This involves feeding the training data to the model and allowing it to learn the relationships between the features and the target variable.
4. **Evaluate the model on the test set.** This involves feeding the testdata to the model and measuring how well it predicts the target variable.

Model evaluation:

1. **Calculate the evaluation metrics.** There are a number of different evaluation metrics that can be used to assess the performance of a machine learning model, such as ***R-squared, mean squared error (MSE), and root mean squared error (RMSE).***

2. **Interpret the evaluation metrics.** The evaluation metrics will give you an idea of how well the model is performing on unseen data. If the model is performing well, then you can be confident that it will generalize well to new data. However, if the model is performing poorly, then you may need to try a different model or retune the hyperparameters of the current model.

Model evaluation:

- Model evaluation is the process of assessing the performance of a machine learning model on unseen data. This is important to ensure that the model will generalize well to new data.
- There are a number of different metrics that can be used to evaluate the performance of a house price prediction model. Some of the most common metrics include:

- **Mean squared error (MSE):** This metric measures the average squared difference between the predicted and actual house prices.
- **Root mean squared error (RMSE):** This metric is the square root of the MSE.
- **Mean absolute error (MAE):** This metric measures the average absolute difference between the predicted and actual house prices.
- **R-squared:** This metric measures how well the model explains the variation in the actual house prices.

In addition to these metrics, it is also important to consider the following factors when evaluating a house price prediction model:

- **Bias:** Bias is the tendency of a model to consistently over- or underestimate house prices.
- **Variance:** Variance is the measure of how much the predictions of a model vary around the true house prices.
- **Interpretability:** Interpretability is the ability to understand how the model makes its predictions. This is important for house price prediction models, as it allows users to understand the factors that influence the predicted house prices.

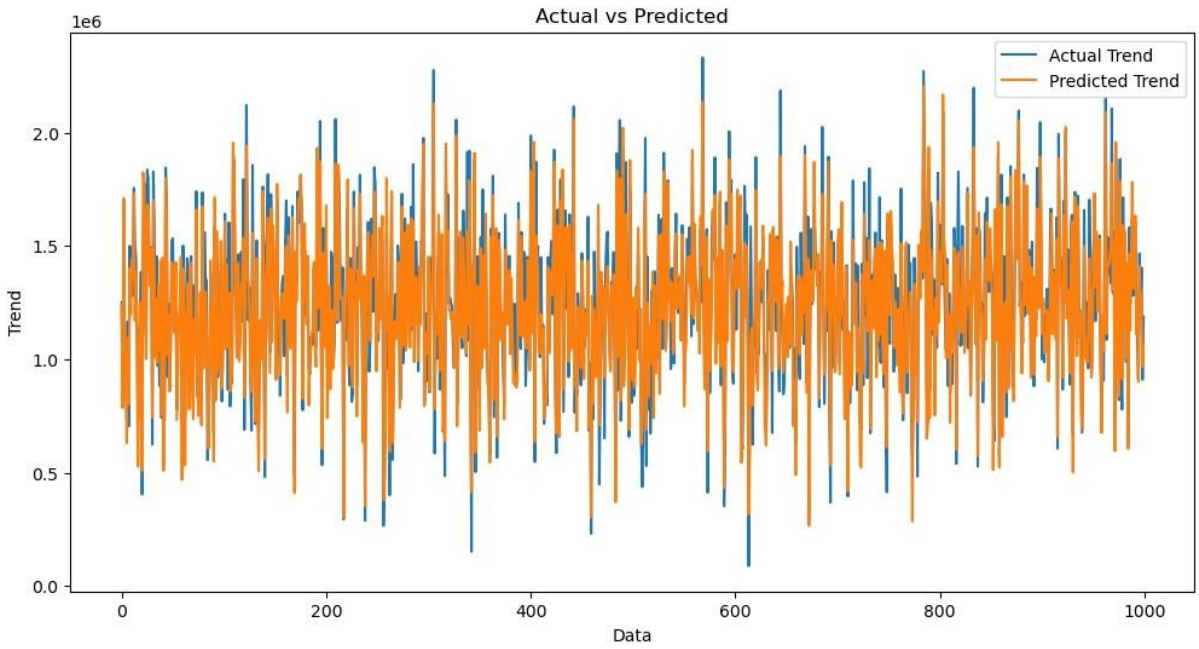
Evaluation of Predicted Data:

In [18]:

```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
plt.plot(np.arange(len(Y_test)), Prediction5, label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('Actual vs Predicted')
```

Out[18]:

Text(0.5, 1.0, 'Actual vs Predicted')

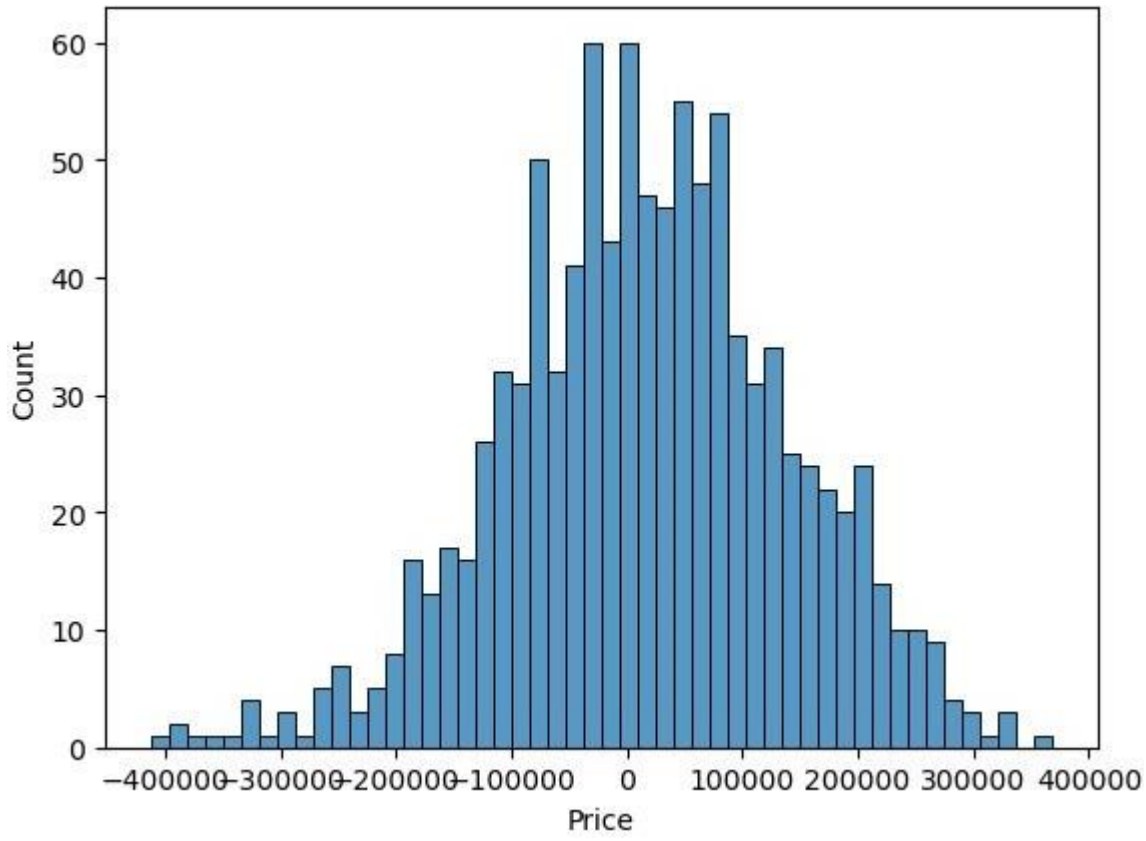


In [19]:

```
sns.histplot((Y_test-Prediction4), bins=50)
```

Out[19]:

<Axes: xlabel='Price', ylabel='Count'>



In [20]:

```
print(r2_score(Y_test, Prediction2))

print(mean_absolute_error(Y_test, Prediction2))

print(mean_squared_error(Y_test, Prediction2))
```

Out[20]:

-0.0006222175925689744

286137.81086908665

128209033251.4034

Model Comparison:

The less the Root Mean Squared Error (RMSE), The better the model is.

In [30]:

```
models.sort_values(by="RMSE (Cross-Validation)")
```

Out[30]:

	Model	MAE	MSE	RMSE	R2 Score	RMSE (Cross-Validation)
6	XGB Regressor	1.743992e+04	7.165790e+08	2.676899e+04	9.065778e-01	29698.849618
4	SVR	1.784316e+04	1.132136e+09	3.364723e+04	8.524005e-01	30745.475239
5	Random Forest Regressor	1.811511e+04	1.004422e+09	3.169262e+04	8.690509e-01	31138.863315
1	Ridge	2.343550e+04	1.404264e+09	3.747351e+04	8.169225e-01	35887.852792

	Model	MAE	MSE	RMSE	R2 Score	RMSE (Cross-Validation)
2	Lasso	2.356046e+04	1.414338e+09	3.760768e+04	8.156092e-01	35922.769369
0	Linear Regression	2.356789e+04	1.414931e+09	3.761557e+04	8.155318e-01	36326.451445
7	Polynomial Regression (degree=2)	2.382228e+15	1.513991e+32	1.230443e+16	-1.973829e+22	36326.451445
3	Elastic Net	2.379274e+04	1.718446e+09	4.145414e+04	7.759618e-01	38449.008646

In [31]:

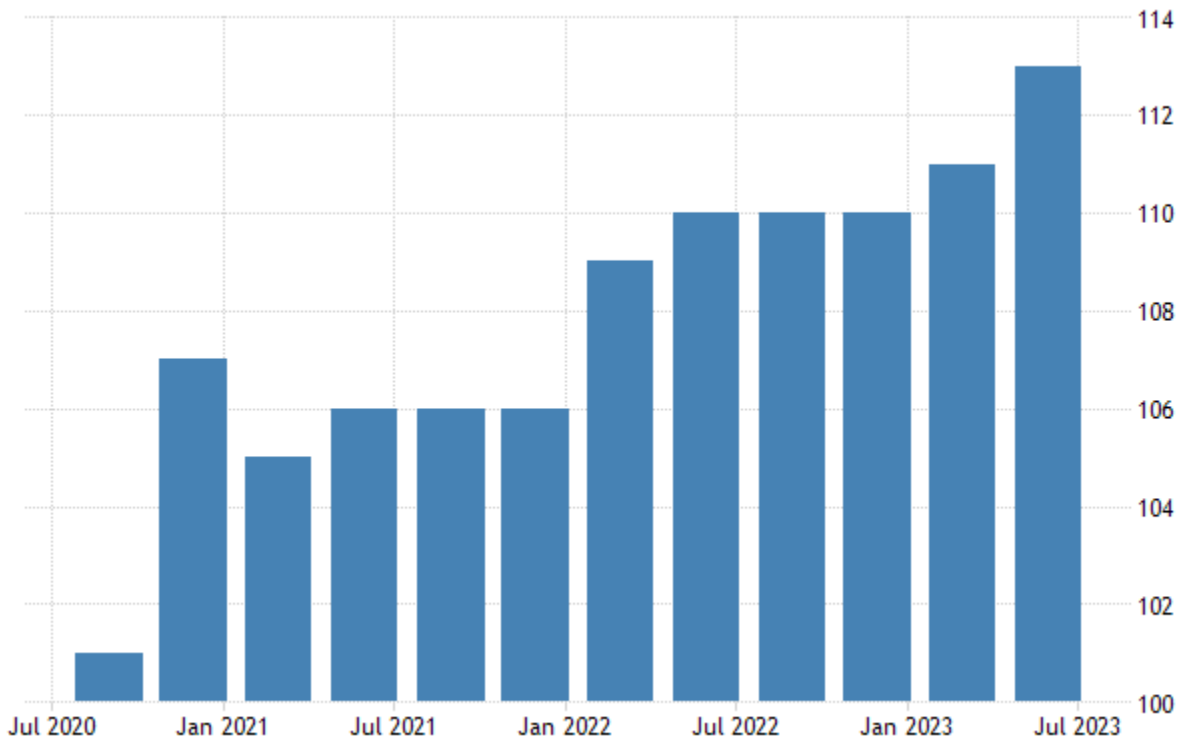
```
plt.figure(figsize=(12,8))

sns.barplot(x=models["Model"], y=models["RMSE (Cross-Validation)"])

plt.title("Models' RMSE Scores (Cross-Validated)", size=15)

plt.xticks(rotation=30, size=12)

plt.show()
```



Feature Engineering:

Feature engineering is a crucial aspect of building a house price prediction model using machine learning. It involves creating new features, transforming existing ones, and selecting the most relevant variables to improve the model's predictive power. Here are some feature engineering ideas for house price prediction:

1. Total Area Features:

Combine individual room areas to create features like "Total Living Area," "Total Bedroom Area," or "Total Bathroom Area." These can be significant predictors of house price.

2. Ratio Features:

Create features that represent ratios, such as the "Bedroom to Bathroom Ratio" or "Living Area to Lot Area Ratio." These ratios may capture the property's layout and functionality.

3. Age of the Property:

Calculate the age of the property by subtracting the construction year from the current year. Newer properties might have higher values.

4. Neighborhood Statistics:

Aggregate neighborhood-level statistics, such as the average income, crime rate, school ratings, or proximity to amenities, and use these as features.

5. Distance to Key Locations:

Calculate distances from the property to essential places like schools, parks, shopping centers, or public transportation hubs. Closer proximity to such amenities can affect the price.

6. Categorical Encodings:

Use techniques like one-hot encoding, label encoding, or target encoding for categorical variables, such as property type, heating system, or garage type.

7. Seasonal Features:

Create features indicating the season during which the house was sold. Seasonality can influence property demand and prices.

8. Historical Data:

Incorporate historical data on house prices and local real estate market trends. This can help the model account for cyclical patterns.

9. Exterior Features:

Develop features related to the property's exterior, such as the presence of a swimming pool, patio, or garden. These features can be valuable for determining a property's appeal.

10. Quality Scores:

Create a combined quality score by aggregating the quality ratings of various components of the property, such as kitchen quality, bathroom quality, and overall house quality.

11. Logarithmic Transformations:

Apply logarithmic transformations to features like "Lot Area" or "Number of Bedrooms" to make their distributions more normal.

12. Interaction Features:

Create interaction terms by multiplying or dividing relevant features. For example, "Number of Bathrooms" multiplied by "Total Living Area" can represent the total bathroom area.

13. Missing Value Indicators:

Create binary indicators for missing values in the dataset. The presence of missing data can be an informative feature.

14. Density Features:

Compute population density in the neighborhood or the density of certain property types. High density might impact property prices.

15. Sentiment Analysis:

Analyze online reviews or social media sentiment related to the property or neighborhood to capture public perception.

16. Time-Related Features:

Incorporate time-related features like day of the week, month, or year when the property was listed or sold.

17. Zoning Information:

Include zoning information that can affect property use, such as residential, commercial, or mixed-use zoning.

18. Accessibility Features:

Create features to represent accessibility, like the number of nearby public transport stations or major highways.

19. Energy Efficiency:

Include features related to energy-efficient components, such as insulation, energy-efficient appliances, or solar panels.

20. Demographic Data:

Use demographic data for the area to understand the potential buyer's income levels, family sizes, and preferences.

Various feature to perform model training:

- **Use a variety of feature engineering techniques.**

Feature engineering is the process of transforming raw data into features that are more informative and predictive for machine learning models. By using a variety of feature engineering techniques, you can create a set of features that will help your model to predict house prices more accurately.

- **Use cross-validation.**

Cross-validation is a technique for evaluating the performance of a machine learning model on unseen data. It is important to use cross-validation to evaluate the performance of your model during the training process. This will help you to avoid overfitting and to ensure that your model will generalize well to new data.

- **Use ensemble methods.**

Ensemble methods are machine learning methods that combine the predictions of multiple models to produce a more accurate prediction. Ensemble methods can often achieve better performance than individual machine learning models.

- **Use cross-validation.**

Cross-validation is a technique for evaluating the performance of a machine learning model on unseen data. It is important to use cross-validation to evaluate the performance of your model during the evaluation process. This will help you to avoid overfitting and to ensure that the model will generalize well to new data.

- **Use a holdout test set.**

A holdout test set is a set of data that is not used to train or evaluate the model during the training process. This data is used to evaluate the performance of the model on unseen data after the training process is complete.

- **Compare the model to a baseline.**

A baseline is a simple model that is used to compare the performance of your model to. For example, you could use the mean house price as a baseline.

- **Analyze the model's predictions.**

Once you have evaluated the performance of the model, you can analyze the model's predictions to identify any patterns or biases. This will help you to understand the strengths and weaknesses of the model and to improve it.

CONCLUSION:

In our pursuit of building a precise and dependable house price prediction model, we've embarked on a comprehensive journey, spanning critical phases from feature selection to model training and evaluation. Each of these stages plays a pivotal role in shaping a model that can offer insightful estimates for one of the most substantial financial commitments people and businesses undertake—real estate transactions.

1. **Model Training**: This is where the model's predictive power takes shape. We've delved into an array of regression techniques, carefully adjusting their parameters to grasp patterns within historical data. This step equips the model with the ability to decipher intricate relationships between features and house prices, enabling it to generalize beyond the confines of the training dataset.
2. **Model Evaluation**: This phase serves as the litmus test for our predictive capabilities. By utilizing metrics such as Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, and R-squared, we've quantified the model's performance. It in stills in us the confidence to rely on the model's predictions and assess its adaptability to unforeseen data.

In the ever-evolving realms of real estate and finance, a robust house price prediction model stands as an invaluable asset. It assists buyers, sellers, and investors in making informed decisions, mitigating risks, and seizing opportunities. As more data becomes accessible and market dynamics evolve, the model can be refined and retrained to uphold its accuracy and relevance.